

Having thus described the invention, it is now claimed:

1. A system for organizing multi-dimensional pattern data into a reduced-dimension representation comprising:

a neural network comprised of a plurality of layers of nodes, the plurality of layers including:

an input layer comprised of a plurality of input nodes,

a hidden layer, and

an output layer comprised of a plurality of non-linear output nodes, wherein the number of non-linear output nodes is less than the number of input nodes;

receiving means for receiving multi-dimensional pattern data into the input layer of the neural network;

output means for generating an output signal for each of the output nodes of the output layer of the neural network corresponding to received multi-dimensional pattern data; and

training means for completing a training of the neural network, wherein the training means includes means for equalizing and orthogonalizing the output signals of the output nodes by reducing a covariance matrix of the output signals to the form of a diagonal matrix.

2. A system according to claim 1, wherein said training means uses backpropagation to iteratively update weights for the links between nodes of adjacent layers.

3. A system according to claim 2, wherein said weights are generated randomly in the interval (W, -W).

4. A system according to claim 3, wherein averaged variance of all dimensions of the multi-dimensional pattern data is:

$$V_{in} = \frac{1}{SP} \sum_{i=1}^S \sum_{p=1}^P (x_{ip} - \langle x_i \rangle)^2$$

, and the elements of the covariance matrix of the output signals of the output nodes are defined by:

$$V_{out, k_1 k_2} = \frac{1}{P} \sum_{p=1}^P (O_{k_1 p} - \langle O_{k_1} \rangle)(O_{k_2 p} - \langle O_{k_2} \rangle)$$

, where  $p=1, 2, \dots, P$ ;

$O_{k_1 p}$  is the output signal of the  $k_1$ th node of the output layer for the  $p$ th input data pattern vector;

$O_{k_2 p}$  is the output signal of the  $k_2$ th node of the output layer for the  $p$ th input data pattern vector;

$\langle O_{k_1} \rangle$  is the average of  $O_{k,p}$  evaluated over the set of input data pattern vectors

$\langle O_{k_2} \rangle$  is the average of  $O_{k,p}$  evaluated over the set of input data pattern vectors

$k_1 = 1$  to  $K$  ;

$k_2 = 1$  to  $K$  ;

$K$  is the number of dimensions in the reduced-dimension representation; and

$\langle \rangle$  denotes the mean evaluated over the set of input data pattern vectors for each indicated component.

5. A system according to claim 4, wherein weights  $\Delta w_{kj}$  between the hidden layer and the output layer are iteratively updated according to the expression:

$$\begin{aligned} \Delta w_{kj} &= -\eta \frac{\partial E}{\partial w_{kj}} = \frac{1}{P} \sum_{p=1}^P \eta \delta_{kp} O_{jp} \\ &= -\eta \left( \frac{\partial E_{kk}}{\partial w_{kj}} + \sum_{k_2=k+1}^K \frac{\partial E_{kk_2}}{\partial w_{kj}} + \sum_{k_1=1}^{k-1} \frac{\partial E_{k_1k}}{\partial w_{kj}} \right) \\ &= \Delta w_{kj,1} + \Delta w_{kj,2} + \Delta w_{kj,3} \end{aligned}$$

, where  $\eta$  is a constant of suitable value chosen to provide efficient convergence but to avoid oscillation;

$O_{jp}$  is the output signal from the  $j$ th node in the layer preceeding the output layer due to the  $p$ th input data pattern vector;

$E$  is the error given by:

$$E = \sum_{k_1=1}^K \sum_{k_2=k_1}^K E_{k_1 k_2}$$

and,

$$E_{k_1 k_2} = \left( \frac{V_{out, kk} - r_{kk} V_{in}}{r_{kk} V_{in}} \right)^2$$

, where  $k_1 = k_2 = k$ ;  $k = 1, \dots, K$ ; and  $r_{kk}$  is a positive constant which has an effect of increasing the speed of training,

$$E_{k_1 k_2} = \left( \frac{V_{out, k_1 k_2}}{r_{k_1 k_2} V_{in}} \right)^2$$

, where  $k_2 > k_1$ ;  $k_1 = 1, \dots, K-1$ ;  $k_2 = k_1 + 1, \dots, K$ ; and  $r_{k_1 k_2}$  is a positive constant which has an effect of increasing the speed of training; and

$\delta_{kp} = \delta_{kp,1} + \delta_{kp,2} + \delta_{kp,3}$ , where  $\delta_{kp}$  is a value proportional to the contribution to the error  $E$  by the outputs of the  $k$ th node of the output layer, for the  $p$ th input data pattern vector, and  $\delta_{kp,1}$ ,  $\delta_{kp,2}$ , and  $\delta_{kp,3}$  are components of  $\delta_{kp}$ .

6. A system according to claim 5, wherein:

$$\Delta w_{kj,1} = -\eta \frac{\partial E_{kk}}{\partial w_{kj}} = \frac{1}{P} \sum_{p=1}^P \eta \delta_{kp,1} O_{jp}$$

$$\Delta w_{kj,2} = -\eta \sum_{k_2=k+1}^K \frac{\partial E_{kk_2}}{\partial w_{kj}} = \frac{1}{P} \sum_{p=1}^P \eta \delta_{kp,2} O_{jp}$$

$$\Delta w_{kj,3} = -\eta \sum_{k_1=1}^{k-1} \frac{\partial E_{k_1k}}{\partial w_{kj}} = \frac{1}{P} \sum_{p=1}^P \eta \delta_{kp,3} O_{jp}$$

where  $\Delta w_{kj,1}$  is the contribution from the diagonal terms of the covariance matrix of the outputs,

$\Delta w_{kj,2}$  is the contribution from the off-diagonal terms in  $k$ th row,

$\Delta w_{kj,3}$  is the contribution from the off-diagonal terms in  $k$ th column, and

$O_{jp}$  is the output signal from the  $j$ th node in the layer preceeding the output layer for the  $p$ th input data pattern vector.

7. A system according to claim 6, wherein:

$$\delta_{kp,1} = 4 (V_{out,kk} - r_{kk} V_{in})(\langle O_k \rangle - O_{kp}) O_{kp} (1 - O_{kp})$$

$$\delta_{kp,1} = 2 \left( \sum_{k_2=k+1}^K V_{out,kk_2} (\langle O_k \rangle - O_{kp}) \right) O_{kp} (1 - O_{kp})$$

$$\delta_{kp,3} = 2 \left( \sum_{k_1=1}^{k-1} V_{out,k_1k} (\langle O_k \rangle - O_{kp}) \right) O_{kp} (1 - O_{kp})$$

, where

$O_{kp}$  is the output signal from the  $k$ th node in the output layer for the  $p$ th input data pattern vector, and

$\langle O_{kp} \rangle$  is the average of  $O_{kp}$  evaluated over the set of input data pattern vectors.

8. A system according to claim 5, wherein backpropagation of error to the weights  $\Delta w_{ji}$  between the  $j$ th node in a layer of nodes and the  $i$ th node in its' preceeding layer:

$$\Delta w_{ji} = \eta \frac{\partial E}{\partial w_{ji}} = \frac{1}{P} \sum_{p=1}^P \eta \delta_{jp} x_{ip}$$

where,  $\delta_{jp}$  is given by:

$$\delta_{jp} = \left( \sum_{k=1}^K \delta_{kp} w_{kj} \right) O_{jp} (1 - O_{jp})$$

9. A method for effecting the organization of multi-dimensional pattern data into a reduced dimensional representation using a neural network having an input layer comprised of a plurality of input nodes, a hidden layer, and an output layer comprised of a plurality of non-linear output nodes, wherein the number of non-linear output nodes is less than the number of input nodes, said method comprising:

receiving multi-dimensional pattern data into the input layer of the neural network;

generating an output signal for each of the output nodes of the neural network corresponding to received multi-dimensional pattern data; and

training the neural network by equalizing and orthogonalizing the output signals of the output nodes by reducing a covariance matrix of the output signals to the form of a diagonal matrix.

10. A method according to claim 9, wherein said step of training includes backpropagation to iteratively update weights for links between nodes of adjacent layers.

11. A method according to claim 10, wherein said weights are generated randomly in the interval (W, -W).

12. A method according to claim 11, wherein averaged variance of all dimensions of the multi-dimensional pattern data is:

$$V_{in} = \frac{1}{SP} \sum_{i=1}^S \sum_{p=1}^P (x_{ip} - \langle x_i \rangle)^2$$

,and the elements of the covariance matrix of the output signals of the output nodes is:

$$V_{out,k_1,k_2} = \frac{1}{P} \sum_{p=1}^P (O_{k_1p} - \langle O_{k_1} \rangle)(O_{k_2p} - \langle O_{k_2} \rangle)$$

,where  $p=1,2,\dots,P$  ;

$O_{k_1p}$  is the output signal of the  $k_1$ th node of the output layer for the pth input data pattern vector;

$O_{k_2p}$  is the output signal of the  $k_2$ th node of the output layer for the pth input data pattern vector;

$\langle O_{k_1 p} \rangle$  is the average of  $O_{k_1 p}$  evaluated over the set of input data pattern vectors

$\langle O_{k_2 p} \rangle$  is the average of  $O_{k_2 p}$  evaluated over the set of input data pattern vectors

$k_1 = 1$  to  $K$  ;

$k_2 = 1$  to  $K$  ;

$K$  is the number of dimensions in the reduced-dimension representation; and

$\langle \rangle$  denotes the mean evaluated over the set of input data pattern vectors for each indicated component.

13. A method according to claim 12, wherein weights  $\Delta w_{kj}$  between the hidden layer and the output layer are iteratively updated according to the expression:

$$\begin{aligned} \Delta w_{kj} &= -\eta \frac{\partial E}{\partial w_{kj}} = \frac{1}{P} \sum_{p=1}^P \eta \delta_{kp} O_{jp} \\ &= -\eta \left( \frac{\partial E_{kk}}{\partial w_{kj}} + \sum_{k_2=k+1}^K \frac{\partial E_{kk_2}}{\partial w_{kj}} + \sum_{k_1=1}^{k-1} \frac{\partial E_{k_1 k}}{\partial w_{kj}} \right) \\ &= \Delta w_{kj,1} + \Delta w_{kj,2} + \Delta w_{kj,3} \end{aligned}$$

, where  $\eta$  is a constant of suitable value chosen to provide efficient convergence but to avoid oscillation;

$O_{jp}$  is the output signal from the  $j$ th node in the layer preceeding the output layer, due to the  $p$ th input data pattern vector;

$E$  is the error given by:

$$E = \sum_{k_1=1}^K \sum_{k_2=k_1}^K E_{k_1 k_2}$$

and,

$$E_{k_1 k_2} = \left( \frac{V_{out, kk} - r_{kk} V_{in}}{r_{kk} V_{in}} \right)^2$$

, where  $k_1 = k_2 = k$ ;  $k = 1, \dots, K$ ; and  $r_{kk}$  is a positive constant which has an effect of increasing the speed of training,

$$E_{k_1 k_2} = \left( \frac{V_{out, k_1 k_2}}{r_{k_1 k_2}} V_{in} \right)^2$$

, where  $k_2 > k_1$ ;  $k_1 = 1, \dots, K-1$ ;  $k_2 = k_1 + 1, \dots, K$ ; and  $r_{k_1 k_2}$  is a positive constant which has an

effect of increasing the speed of training; and

$\delta_{kp} = \delta_{kp,1} + \delta_{kp,2} + \delta_{kp,3}$ , where  $\delta_{kp}$  is a value proportional to the contribution to the error  $E$  by the outputs of the  $k$ th node of the output layer, for the  $p$ th input data pattern vector, and  $\delta_{kp,1}$ ,  $\delta_{kp,2}$ , and  $\delta_{kp,3}$  are components of  $\delta_{kp}$

14. A method according to claim 13, wherein:

$$\Delta w_{kj,1} = -\eta \frac{\partial E_{kk}}{\partial w_{kj}} = \frac{1}{P} \sum_{p=1}^P \eta \delta_{kp,1} O_{jp}$$

$$\Delta w_{kj,2} = -\eta \left( \sum_{k_2=k+1}^K \frac{\partial E_{kk_2}}{\partial w_{kj}} \right) = \frac{1}{P} \sum_{p=1}^P \eta \delta_{kp,2} O_{jp}$$

$$\Delta w_{kj,3} = -\eta \left( \sum_{k_1=1}^{k-1} \frac{\partial E_{k_1k}}{\partial w_{kj}} \right) = \frac{1}{P} \sum_{p=1}^P \eta \delta_{kp,3} O_{jp}$$

where  $\Delta w_{kj,1}$  is the contribution from the diagonal term,

$\Delta w_{kj,2}$  is the contribution from the off-diagonal terms in  $k$ th row, and

$\Delta w_{kj,3}$  is the contribution from the off-diagonal terms in  $k$ th column.

15. A method according to claim 14, wherein  $\delta_{kp,1}$ ,  $\delta_{kp,2}$  and  $\delta_{kp,3}$  are given

by:

$$\delta_{kp,1} = 4(V_{out,kk} - r_{kk} V_{in})(\langle O_k \rangle - O_{kp}) O_{kp} (1 - O_{kp})$$

$$\delta_{kp,1} = 2 \left( \sum_{k_2=k+1}^K V_{out,kk_2} (\langle O_k \rangle - O_{kp}) \right) O_{kp} (1 - O_{kp})$$

$$\delta_{kp,3} = 2 \left( \sum_{k_1=1}^{k-1} V_{out,k_1k} (\langle O_k \rangle - O_{kp}) \right) O_{kp} (1 - O_{kp})$$

, where

$O_{kp}$  is the output signal from the  $k$ th node in the layer preceeding the output layer for the  $p$ th input data pattern vector, and

$\langle O_{kp} \rangle$  is the average of  $O_{kp}$  evaluated over the set of input data pattern vectors.

16. A method according to claim 13, wherein backpropagation of error to the weights  $\Delta w_{ji}$  between the  $j$ th node in a layer of nodes and the  $i$ th node in its' preceeding layer are:

$$\Delta w_{ji} = \eta \frac{\partial E}{\partial w_{ji}} = \frac{1}{P} \sum_{p=1}^P \eta \delta_{jp} x_{ip}$$

where,  $\delta_{jp}$  is given by:

$$\delta_{jp} = \left( \sum_{k=1}^K \delta_{kp} w_{kj} \right) O_{jp} (1 - O_{jp})$$

17. A system for organizing multi-dimensional pattern data into a reduced dimensional representation comprising:

a neural network comprised of a plurality of layers of nodes, the

plurality of layers including:

an input layer comprised of a plurality of input nodes, and

an output layer comprised of a plurality of non-linear output

nodes, wherein the number of non-linear output nodes is less than the number of input nodes;

receiving means for receiving multi-dimensional pattern data into the

input layer of the neural network;

output means for generating an output signal at the output layer of the

neural network corresponding to received multi-dimensional pattern data; and

training means for completing a training of the neural network, wherein the training means conserves a measure of the total variance of the output nodes, wherein the total variance of the output nodes is defined as:

$$V = (1/P) \sum_{p=1}^{P} \sum_{i=1}^S (x_{ip} - \langle x_i \rangle)^2$$

, where  $\{x_p\}$  is a set of data pattern vectors;

$p = 1, 2, \dots, P$ ;

$P$  is defined as a positive integer;

$\langle x_i \rangle$  denotes the mean value of  $x_{ip}$  evaluated over the set of data pattern vectors;

$S$  is the number of dimensions;

$x_{ip}$  is the  $i$ th component of  $x_p$ , the  $p$ th member of a set of data pattern vectors.

18. A system according to claim 17, wherein said training means completes the training of the neural network via backpropagation for progressively changing weights for the output nodes.

19. A system according to claim 18, wherein said training means further

includes,

means for training the neural network by backpropagation by progressively changing weights  $w_{kj}$  at the output layer of the neural network in accordance with,

$$\Delta w_{kj} = (1/P) \sum_{p=1}^{p=P} \Delta w_{p,kj} = (1/P) \sum_{p=1}^{p=P} \eta \delta_{pk} O_{pj}$$

, where  $O_{pj}$  is the output signal from the  $j$ th node in the layer preceeding the output layer due to the  $p$ th data pattern,

$\eta$  is a constant of suitable value chosen to provide efficient convergence but to avoid oscillation, and

$\delta_{pk}$  is a value proportional to the contribution to the error  $E$  by the outputs of the  $k$ th node of the output layer for the  $p$ th input data pattern.

20. A system according to claim 19, wherein:

$$\delta_{pk} = [V - (1/P) \sum_q \sum_n (O_{qn} - \langle O_n \rangle^2)] (O_{pk} - \langle O_k \rangle) O_{pk} (1 - O_{pk})$$

21. A system according to claim 19, wherein said neural network further comprises at least one hidden layer comprised of hidden nodes, wherein adaptive weights  $w_{ji}$  for each hidden node is progressively improved in accordance with,

$$\Delta w_{ji} = -\eta \frac{\partial E}{\partial w_{ji}} = \frac{1}{P} \sum_{p=1}^{p=P} \eta \delta_{pj} O_{pi}$$

, where  $O_{pi}$  is the output signal for the  $i$ th node of the layer preceeding the  $j$ th layer of the  $p$ th input data pattern.

22. A system according to claim 21, wherein:

$$\delta_{pj} = \left( \sum_{k=1}^K \delta_{pk} w_{kj} \right) O_{pj} (1 - O_{pj})$$

23. A method for effecting the organization of multi-dimensional pattern data into a reduced dimensional representation using a neural network having an input layer comprised of a plurality of input nodes, and an output layer comprised of a plurality of non-linear output nodes, wherein the number of non-linear output nodes are less than the number of input nodes, said method comprising:

receiving a set  $\{x_p\}$  of data pattern vectors into the input layer of the neural network, wherein  $p=1,2,\dots,P$  and wherein  $P$  is defined as a positive integer, and wherein the set of data pattern vectors has a total variance defined as,

$$V = (1/P) \sum_{p=1}^{p=P} \sum_{i=1}^{i=S} (x_{ip} - \langle x_i \rangle)^2$$

, where  $\{x_p\}$  is a set of data pattern vectors;

$p=1,2,\dots,P$ ;

$P$  is defined as a positive integer;

$\langle x_i \rangle$  denotes the mean value of  $x_{ip}$  evaluated over the set of data pattern vectors;

$S$  is the number of dimensions;

$x_{ip}$  is the  $i$ th component of  $x_p$ , the  $p$ th member of a set of data pattern vectors;

training the neural network by backpropagation; and

displaying a multi-dimensional output signal from the output layer of the

neural network.

24. A method according to claim 23, wherein said step of training the neural network by backpropagation includes progressively changing weights  $w_{kj}$  at the output layer of the neural network in accordance with,

$$\Delta w_{kj} = (1/P) \sum_{p=1}^{p=P} \Delta w_{p,kj} = (1/P) \sum_{p=1}^{p=P} \eta \delta_{pk} O_{pj}$$

, where  $O_{pj}$  is the output signal from the  $j$ th node in the layer preceeding the output layer due to the  $p$ th data pattern, and

$\eta$  is a constant of suitable value chosen to provide efficient convergence but to avoid oscillation.

$\delta_{pk}$  is a value proportional to the contribution to the error  $E$  by the outputs of the  $k$ th node of the output layer for the  $p$ th input data pattern.

25. A system according to claim 24, wherein:

$$\delta_{pk} = [V - (1/P) \sum_q \sum_n (O_{qn} - \langle O_n \rangle^2)] (O_{pk} - \langle O_k \rangle) O_{pk} (1 - O_{pk})$$

26. A method according to claim 23, wherein said neural network further comprises at least one hidden layer comprised of hidden nodes, wherein adaptive weights  $w$  for each hidden node of the neural network is progressively improved in accordance with,

$$\Delta w_{ji} = -\eta \frac{\partial E}{\partial w_{ji}} = \frac{1}{P} \sum_{p=1}^{p=P} \eta \delta_{pj} O_{pi}$$

, where  $O_{pi}$  is the output signal for the  $i$ th node of the layer preceeding the  $j$ th layer of the  $p$ th input data pattern.

27. A method according to claim 26, wherein

$$\delta_{pj} = \left( \sum_{k=1}^K \delta_{pk} w_{kj} \right) O_{pj} (1 - O_{pj})$$

28. A method according to claim 23, wherein said multi-dimensional output signal is a two-dimensional output signal.

29. A method according to claim 23, wherein said two-dimensional output signal includes data points plotting in relation to 2-dimensional axes.

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